

# A New Hybrid Proposed Algorithm for Multiple Vehicle Detection and Tracking in a Day-Time Environment



D. Sudha, Member, J. Priyadarshini

**Abstract:** Multiple Vehicle detection and tracking is one of the hot research topics in the field of intelligent transportation systems, image processing, computer vision, robotics whereas applications are real time traffic monitoring, lane estimation, accident avoidance, alarm signal to indicate road accidents to save the public safety and so on. There exists a numerous higher level applications are motivated by a young researchers and scientists to identify the newly advanced techniques in which to solve the real time traffic problems using machine learning and deep learning methods to track multiple vehicles accurately. To addresses the various existing challenges in machine learning and deep learning based multiple vehicle detection and tracking algorithms namely camera oscillation, shadowing, changing in background motion, cluttering, camouflage etc. for the detection rate decreases dramatically when the distribution of the training samples and the scene target samples do not match. To address this issue, a new hybrid model of two-tier classifier of Haar+HOG, SVM+AdaBoost classifier algorithm based on a feature extraction algorithm is proposed in this paper. Inspired by the Adaptive Discrete Classifiers mechanism multiple relatively independent source samples are first used to build multiple classifiers and then particle grouping is used to generate the target training samples with confident scores. The global manual feature extraction ability of deep convolutional neural network is then used to perform source-target scene feature similarity calculation with a deep auto encoder in order to design a composite deep structure based adaptive discrete classifier and its global training method. The main contributions of this paper are threefold: 1) To improve the overall accuracy rate of multiple vehicle detection and tracking of front-view vehicles alone rather than full-sided vehicles. 2) The novelty of our proposed work is for particle grouping of multi-vehicles such as car, bus and lorry. 3) To propose the tracking of front-view multi-vehicles in linear and non-linear motion using particle and extended kalman filter along with hybrid new multi-vehicle tracking algorithm and attains 93.6% of accuracy is shown in the experimental results. We evaluates our proposed method with standard data sets PETS 2016 and 5 self-data sets iROAD were manually collected on traffic road and compared with the existing state of the art approaches and along with the Experiments on the Kitti dataset and a 3 different self-data set captured by our group demonstrate that the proposed method performs better than the existing machine-learning based vehicle detection methods.

In addition, compared with the existing automatic feature extraction and region based object detection methods, our new hybrid method improves the overall detection rate by an average of approximately 5% of existing methods.

**Index Terms:** Multi-Vehicle Detection, AdaBoost Classifier, Deep Learning, Haar trainer, Particle grouping, Extended Kalman Filter.

## I. INTRODUCTION

Intelligent Transportation systems (ITS) aim to reduce the fatality ratio and enable to provide public safety and population incorporated with secure transportation networks. The important tasks in ITS filed is to detect and track between the two images of the same object or scene; these applications can include object detection, tracking, hand recognition, wheel classification, 3-d is modelling of gesture recognition, vehicle detection and so on. In order to focus on the guarantee of public safety on the road, it makes an absolute necessary for intelligent vehicles to detect and track in an efficient manner using the unique considerable algorithms and classifiers. To design such a training algorithm and datasets that is neither distracting nor bothersome, these systems must act with the dynamic environment wherein situations like illumination conditions, cluttering, scale and camouflage etc. By attaining better detection results, features are extracted properly from multiple vehicles and also training algorithms were tested with the haar, SVM, HOG with object detection engine. This paper deals with the real time of intelligent transportation research (ITS) and computer vision approaches for multiple vehicle detection and tracking of front side of the car, bus, truck and lorry present in an on road environment with higher resolution cameras. Feature extraction or dimensionality reduction plays a vital role in obtaining an accurate detection and tracking. Global features are extracted properly and trained has given to the system for automation of detection accurately. The prominent features are manually chosen according to the objects such as cars width, length, no of mirrors, wheels, side-mirror etc., and move in into deep learning concepts. The highlighted tasks are the use of more parameters for getting an accurate result in multiple vehicle detection in input video/images. In addition to tracking multiple vehicles, we also assign labels to each track to differentiate the types of the vehicles from the remote object detection engine. This could be used to influence the behaviour of an automated system, depending on the application criteria, whether a certain object is detected or not in motion.

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The main contribution of this paper are as follows, we introduce the problem of multiple vehicle detection and tracking under various illumination conditions like shadowing, camouflage, background, cluttering, camera oscillations and environmental effects etc., and list some common challenges and pitfalls. Motivated by the state of the art detectors and trackers for single object detection and tracking. We propose a combined integrated framework for multiple vehicle detection and classifier algorithms for improving the overall performance of car, bus, truck and lorry on the road. Finally, we compare with three different private data sets and note a considerable amount of gain in tracking performance. This validates the treatment of vehicle detection and tracking as a separate case of multiple objects.

The remainder of this paper is organized as follows. Section II discusses with the related work in the field of ITS. Section III explains the detailed description of proposed architecture and techniques involved in the multiple vehicle detection and tracking on the road. Section IV relates to the experimental setup, results and discussions. Section V provides concluding remarks.

## II. RELATED WORK

Niluthpol Chowdhury Mithun et al. (2012) [1] implemented the multiple time-spatial images for detection and classification of vehicles from video. The accuracy of vehicle detection was achieved better results when compared with the online method as well as there is a lack of training model to classification of multiple vehicles from a given video. The methods of using multiple TSIs provides the opportunity to identify the latent occlusions among the vehicles and to reduce the dependencies of the pixel intensities between the still and moving objects to increase the accuracy of detection performance as well as to achieve an improved classification performance. Our method focused on the results of multiple vehicle detection and tracking of learning algorithms with multi-layer perceptron algorithm yields more robust accuracy of training which is for system automation of detection using global model for car, bus, truck and lorry with global features involved in multiple tracking. Vinh Dinh Nguyen et al. (2013) [2] had focused on the detection of multiple vehicles by using a turn-back genetic algorithm (GA) and prevents false detection by the method of using motion detection. The drawback was found that Evolutionary Algorithm based methods for vehicle detection cannot achieve high performance because of their fitness functions depend on sensitive information, such as edge or color information on the preceding vehicle. To overcome the existing drawback genetic algorithm are used to increase performance level using disparity map, motion information criteria. The proposed method contributes for the multiple vehicle detection and tracking in moving environment using haar trainer followed by discrete adaptive boost classifier for system automation. Due to the automation of system, in which detection rate yields more accuracy than offline detection mechanism. Bin Tian et al. (2014) [3] had addresses the problem of rear-view vehicle detection and tracking method mainly based on multiple vehicle salient parts using a stationary camera. The merit of the methods are rear view of each part is inferred posteriorly but limitation exists in parameters of feature selection. To

overcome the limitations of parameters in existing methods, our proposed method provides the necessary parameters of selecting the right feature in order to train the system automation for detection of each vehicle like car, bus, truck and lorry in moving environment with several climatic conditions. Qi Zou et al. (2015) [4] presented the work on robust night time vehicle detection system by detecting, tracking, and grouping headlights by the method of training adaboost classifiers for headlight detections. The advantage of the method was false alarm reduced by reflections. Along with learning based detection, context-sensitive tracking and graphic model based headlight pairing. The drawback found that there is a need of occlusion in moving vehicle conditions for predicting the accuracy of detection and tracking in cluttered environment. There exists some limitations to overcome the previous works had been discussed in various condition, our method concentrates the multiple vehicle detection and tracking in terms of handling occlusion under varying illumination condition. The key merit of the proposed work is training and testing done for system automation to detect each vehicle with less false positive rate to obtain the better accuracy with different datasets of multiple given input videos for comparison with the yielded results Ye Li, Meng et al. (2015) [5] delivered the solutions of object tracking using multi scale features that was local and global features to detect multiscale vehicles. The benefit over the method was handled with partial vehicle occlusion with various vehicle shapes. The limitations exists collision among multiple vehicles templates and flatness of sketch. Though existing problems are resolved by our method were focused on multiple vehicle detection and tracking using training for global model of all vehicles and detection using particle grouping and extended multiple process to multiple vehicle tracking in moving environment with machine learning algorithms with filtering techniques. Liang-Chien Liu et al. (2015) [6]. had addressed for lane marking detection, vehicle tracking, and distance estimation used by forward collision avoidance assist system. The benefit of the method achieved robust accuracy of tracking but the constraints over here was missing of accuracy representation in terms of false positive rate and negative rate. Meanwhile, our method delivered the multiple vehicle detection and tracking in terms of performance measures using precision and recall with false positive rate and negative rate of detection and tracking for car, bus, truck and lorry in a dynamic environment. Xuezhi Wen et al. (2015) [7] delivered the techniques were Haar-like feature selection and classification for vehicle detection with effective feature selection method via AdaBoost by combining a sample's feature value with its class label. The advantage of this framework exhibits to speed up the feature selection processes and to reduce the inter class variability. The proposed framework concentrates the methods of multiple vehicle detection and tracking in a dynamic environment of car, bus, truck and lorry in which different frames are splits into equal size of .jpeg images and computes the stored features for vehicle detection used by haar training followed by discrete adaptive boost classifier for detection with particle grouping of each objects along with tracking used by particle and kalman filter with multi-layer perceptron algorithm.

Xiao Liu et al. (2015) [8] focused on the work of tracking multiple objects by detection. With the novelty of existing works with benefits were decreased the post-processing mistake risk and to improve performance in tracking. The limitations exists in the work were entire model training into a convex optimization problem and estimate its parameters using the cutting plane optimization in crowded scenes environment alone. The framework of our proposed work is to overcome the limitations by using the training with creation of global model for car, bus, truck and lorry in a dynamic environments under varying illumination conditions which is mainly for multiple vehicle detection and tracking in different dataset testing with the predicted results of accuracy in terms of performance measures like precision, recall, false positive rate and true positive rate exists. Ravi Kumar Satzoda et al. (2016) [9] had addressed the work of Vehicle Detection using Active learning and Symmetry. VeDAS is a multipart-based vehicle detection algorithm that employs Haar-like features and Adaboost classifiers for the detection of fully and partially visible rear views of vehicles. There exists the detected parts from the classifiers are associated by using a novel iterative window search algorithm and a symmetry-based regression model to extract fully visible vehicles. The merit of this work is high true positive rates of over 95% and performs better than rear-view-based vehicle detection methods. The limitations are found that fully visible vehicle under occlusions are missing. To overcome those limitations of existing issues, our proposed method incorporated into multiple vehicle detection and tracking of car, bus, truck and lorry of fully visible vehicles in a dynamic environment by feed forward neural network with filtering techniques exists. Ricardo Omar Chavez-Garcia and Olivier Aycard (2016) [10] had presented the novelty of accurate detection and classification of moving object. The tracking stage benefits from the reduction of mis-detections and more accurate classification information to accelerate the tracking process. The limitations exists in that no training model for detection and classification so that to overcome the existing limitations our method demonstrated that training model for multiple vehicle objects like car, bus, truck and lorry using haar trainer followed adaptive boost classifier to extract the features in a global manner to detect the objects in a given input video. Hulin Kuang et al. (2017) [11] had conveyed the work for night time vehicle detection system by combined a novelty of bio inspired image enhancement approach with a weighted feature fusion technique. The benefit in that vehicle detection method was performed the accuracy of 95.95% detection rate at 0.0575 false positives per image. Though, the benefits attained for night time vehicle detection but some of the limitations were found that partly occluded and distant vehicles are missed occasionally. To overcome these issues, the proposed framework shows that multiple vehicle detection and tracking in a dynamic environment by training a system model for object detection with global parameters of each vehicle. With that we move on to the multiple tracking vehicles under all types of environmental scenarios like sunny, rainy, night time, day time input videos were tested. Huijing Zhao et al. (2017) [12] delivered the work for analysis of lane changes on road by trajectory collection with multiple horizontal 2-D lidars of 360 degree coverage. The performance was tested with Fourth Ring Road in Beijing for a total distance of 64 km, with more than 5700 environmental trajectories with a total

length of over 19 h. The collection of trajectories information is automated by the system is the major benefit of the novelty. The limitations found that there is a lack of occlusion among them. If there exists an occlusion on road then there may a loss of deviations in analysing trajectory changes on road. The proposed work focuses on multiple vehicle detection and tracking under complex environments with the experimental results obtained the accuracy rate of detection and tracking. Yanjie Yao et al. (2017) [13] proposed the techniques of convolutional neural network for multiple vehicle detection and classification with prior objectness measure. The benefit of this method achieved a more accurate vehicle detection process is faster than neural network. The limitations exists there is no training method for vehicle detection and tracking. Our method deliberates the training model for system automation of car, bus, truck and lorry using haar trainer and discrete adaptive classifier also with particle filter, kalman filter, distance formulation technique, multiple vehicle tracking algorithm etc., to detect and track multiple vehicles in moving environment. With the results of multiple objects yields more accuracy of precision and recall respectively. Vinh Dinh Nguyen et al. (2017) [14] presented the methods of a novel deep learning approach with the use of multiple sources of local patterns and depth information to yield robust on-road vehicle and pedestrian detection, recognition and tracking of adaptive U-V disparity algorithm was used. The merit of these works were consideration of multiple local patterns and depth information operated successfully. The drawback exists collisioning of pedestrians and vehicles were not evaluated. In the proposed framework addressed the problems of multiple vehicle detection and tracking on road with collision and occlusion among them with the help of various methods follows such as bus topology and distance formulation techniques along with potential and kinetic energy calculation of predicting collision among them. Carlos Cuevas et al. (2017) [15] contributed the work on efficient and high quality strategies to detect stationary foreground objects, which was able to detect not only completely static objects but also partially static ones. The work in which involves three parallel nonparametric detectors with different absorption rates that are used to detect currently moving foreground objects, short-term stationary foreground objects, and long-term stationary foreground objects. The limitations of these works are fused to multi layered stationary objects and then occlusions are missing. Our method deliberates the multiple vehicle detection and tracking with occlusion in linear and non-linear motion using particle and kalman filtering techniques and also integrated global features for given training to the system automation in which included the local and global features under varying illumination conditions were tested with the different testing and training datasets as well as to predicted the accuracy of each vehicle in terms of precision and recall with representation of plots. Bo-Hao Chen et al. (2018)[7] has presented a sparse and low rank constraint model by using a contextual regularization approach for motion object detection. The benefit of this model yields more performance rate in single scenario alone hence there is a problem of finding multiple moving object detection in multiple scenario is challenging one.

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To overcoming this problems our proposed method tested with the different datasets with occlusion and results are shown in the multiple scenarios of car race and multiple vehicles moving on road. Zhipeng Deng et.al (2018)[8] described the novelty of vehicle detection on region based convolutional neural networks(R-CNNs) in which combined a hierarchial feature maps to detect small object accurately.

The combination of accurate vehicle proposed network with vehicle attribute learning network to found vehicles location and its attributes. Eventhough the vehicle detection mapped with the feature of objects there is a lack of training for the object detection engine and missed the linearity and non linearity motion on road. In our method we addressed the existing problems and shown in the experimental results using different datasets. Keyu Lu et.al (2018)[9] has came up with the sparse window techniques to reduce the number of input image patches without accuracy. It cause a more drift in multiple vehicle detectors .Consequently parameter is too limited not fit for solving real time problems on/off road in multiple vehicles. In our proposed method solved the problems of multiple vehicle detection in the presence of occlusion and tested the performance of multiple objects/vehicles is shown in the results. Yingfeng et.al (2017)[10] has used a scene adaptive vehicle detection algorithm based on a composite deep structure using Bagging method. The limitation found that only generation of target training samples with confidence scores so that it is

not suitable for system automation to detect and track multiple vehicles on road or dynamic environment. To overcome the existing issues, our method satisfies with the multiple object tracking using haar trainer paired with adaptive discrete boost classifier and filters for linear and non-linear motion on road. To sum up, existing approaches have several problems in multiple vehicle detection and tracking due to its various pitfalls like illumination changes, cluttering, motions, environmental aspects, aspect ratio, camera motion etc., and so on. After evaluating the literature review we came across the methods for detecting multiple objects accurately using machine learning concepts with deep learning parameters of several features in each vehicles .Even though the machine learning methods have been adopted to detect and track multiple vehicles but it requires more computing resources than deep learning methods .Our proposed methods focused on the system automation of multiple vehicle detection and tracking in a dynamic environment and evaluate the performance with the datasets and calculate its accuracy using precision and recall for vehicle detection of car, bus, truck and lorry in an input video. For that classifier and training algorithms were considered together with multiple vehicle detection by tracking using filtering and neuro fuzzy inference system are incorporated.



**Fig.1. Illustrates various scenarios in which multiple vehicles moving on-road in the first row and varying illumination changes in the second row due to its environmental conditions like rainy, midst and sunny**

### III. PROPOSED WORK

The proposed architectural method describes about multi-vehicle detection and tracking in a day time environment in which comprises of 5 different layers namely input layer, training and testing layers, Particle grouping layer, vehicle detection layer and multi-vehicle tracking layer. The initial step is to feed input into the system and then splits into frames of 45 fps into .jpeg images. For training and testing layer, creation of public and self- datasets have been constructed a global system model in which collection of positive and negative samples were taken and given train to the system using the hybrid model of haar trainer paired with adaboost classifier and HOG with Linear SVM. The

third layer is a particle grouping layer in which the computed features are taken within a region of interest

rather than the entire frame and follows multi- vehicle object detection using feature based detection using Haar+Adaboost and HoG+SVM of global training model of each vehicle like car, bus, truck and lorry moving on-road. Finally, Multi-vehicle tracking layer exists in which filtering techniques were involved in linear motion using particle filter and extended kalman filter is for non-linear motion tracking.

Video is given as an input to the system and it is converted to a sequential set of frames. In the proposed system the object to be tracked is a car, bus, truck and lorry from the given input.

Every tracking method requires an object detection mechanism either in every frame or when the object first appears in the video. A common approach for object detection is to use information in a single frame. Generally, object detection can be achieved by building a representation of the scene called the background model and then finding deviations from the model for each incoming frame. Any significant change in an image region from the background model signifies a moving object. But a serious flaw of this approach is that the background cannot be modeled in a generic manner and added to that, changing backgrounds would lead to an increase in the false positive rate. Thus there is a necessity for a generic and the optimal object detection engine to meet the requirements of an efficient tracking system.

#### Step 1: Input Layer

A video is read at the input which is then split into a set of frames at the rate of 20 frames per second. These video sequences are given as input to the object detection layer.

#### Step 2: Object Detection Layer

The supervised learning approach is used in order to train the system with the target object for automatic detection. The Haar training approach is used which is followed by a strong classification method using the Adaptive boost classifier. The result of this engine is the coordinate of the bounding rectangle box that encloses the object. After particle grouping, each group is associated with a descriptor value and the strength of identity and it is computed based on the visual cues of the object. The maximum identity strength group is used for identifying the whole object uniquely. Further processing of the object is done only using this identified particle group. Edge detection for the pixels in the identified particle groups is done and then the array values are binary coded and stored. Only the binary values are stored because in case the object moves out of frame and re-appears a few seconds later, it is identified correctly and matched using this binary value. This proves to be useful whenever an existing object reappears in the scene. This identity recognition is done initially by identifying the objects in the scene. As an example, in a car race, all the cars participating in the race are identified uniquely by corresponding particle groups. Since the cars and the number of cars are known at the start itself, the identity recognition is done at the start and no later.

Using the coordinates of the particle groups identified the bus along with the links to the objects in a scene is created. The line connecting the object to the bus is referred to as the link. This varies from frame to frame depending upon the position and presence of the object under motion. The aim of an object tracker is to generate the trajectory of an object over time by locating its position in every frame of the video. An object tracker may also provide the complete region in the image that is occupied by the object at every time instant. The tasks of detecting the object and establishing a correspondence between the object instances across frames can either be performed separately or jointly. In the first case, possible object regions in every frame are obtained by means of an object detection algorithm, and then the tracker corresponds to objects across frames. In the latter case, the object region and correspondence is jointly

estimated by iteratively updating object location and region information obtained from previous frames. Tracking the object's true position is done by following its state. This uses information from the object's features and the previous object state to create an estimate of the object's new state. The combination of previously estimated object dynamics and current measurements helps eliminate noise from measurements that would otherwise lead to erratic object tracking. As a simple example, knowing the previous position and velocity of a car allows us to give a rough estimate of its current position. When combining this estimate with additional information of its state, tracking accuracy can be overall improved.



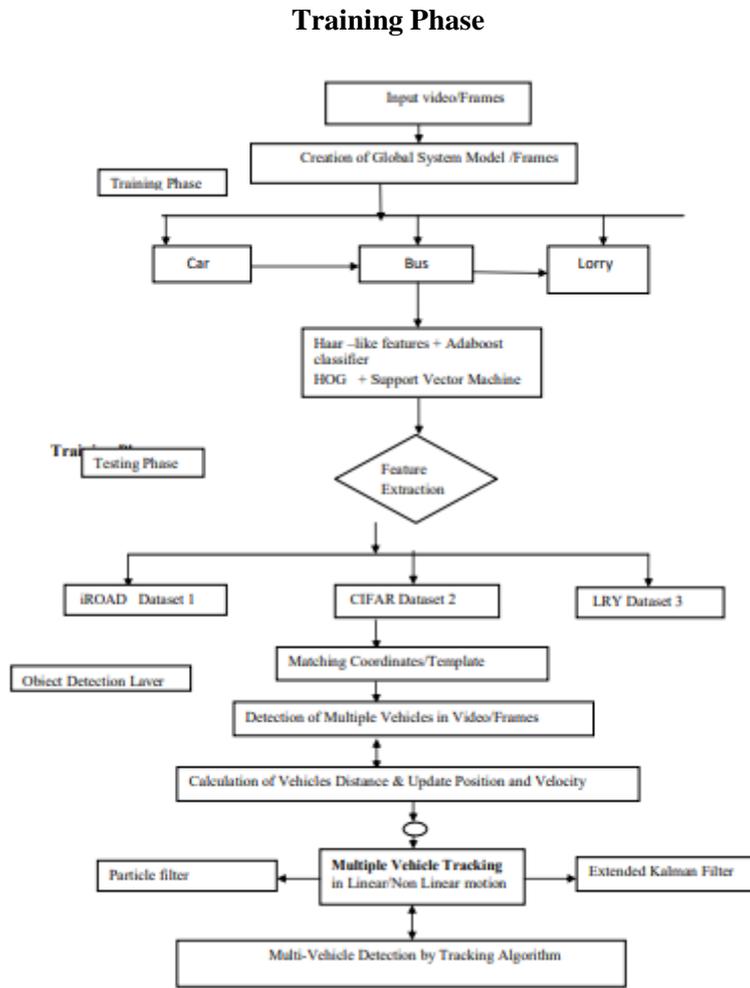


Fig:2 Architecture Diagram of Multi-Vehicle Detection and Tracking

A simple rectangular Haar-like feature considers adjacent rectangular regions, at specific locations where objects are from the frame, sums up the pixel intensities of those regions and calculate the difference between the rectangular regions. Video is given as an input contains multiple vehicles like car, bus, truck and lorry along with animals crossing on the road with varying illumination conditions. Our proposed method concentrates on the global system automation for various kinds of multiple vehicles like car, bus and lorry exists in a linear and non-linear motion on road. An architectural diagram represents that the different layers are present in the detection and tracking techniques exist.

**Algorithm 1: Hybrid Multi-Vehicle Detection and Tracking Algorithm**

Input: Traffic Video of moving on-road day time environment of 35 fps

Output: Multi-Vehicle Object Detection of car, bus, truck and lorry  $N_{th}$  frame in a video, where  $c_{mn}$ , represents car,  $t_{mn}$ ,  $b_{mn}$  and  $l_{mn}$ , represents truck, bus and lorry respectively

**Initialize:**

**for**  $i=1$  to  $n$  **do**

    Read sample  $x_i=(m_i, n_i)$

    Update haar trainer adaboost classifier with svm classifier  $N_{on}$

**end for**

save model  $N_{on}$

**While**  $(f_n)$ :

    On-Line training detection

$N_{off}(f_n):x_{mn}=(c_{mn}, t_{mn}, b_{mn}, l_{mn})$

**Kalman filter Process:**

**Prediction**

**phase:**

$$X_{pk} = (c_{pk}, t_{pk}, b_{pk}, l_{pk}) = (FI X_{(k-1)} + X_{(k)}) + Q$$

//Rewrite

Final result of frame  $x$ :  $S_{fn} = X_{mn}$

**Update Phase:**

```

if  $N_{on}(f_n)$  for each vehicle in FI
else
     $N_{off}(f_n)$ 
    Find result of detection of
    frame  $X_{mn}: c_{mn} \& \& t_{mn} \& \& b_{mn} \& \& l_{mn}$ 
end if
end while
    
```

The training and classification is done by Haar Training and Ada Boost Classifier. The proposed system improves the output by enhancing the existing Haar training method using the Adaboost classifier. The Haar trainer's a weak learner because its detection quality is slightly better than random guessing. In spite of this, the training technique is still preferred. Wavelet coding is suitable for the applications where tolerable degradation and scalability are important. In this Fig.2 describes the training and detection phase of the framework involves a large set of positive and negative images is collected. A positive image is the one that has the desired target depicted in it while a negative image is one that does not have the target. As a simple example for car tracking, an image of a car is said to be positive image while an image of an empty race track or even any other vehicle is considered to be a negative image. After image acquisition, the object marking is necessary. The object marking is done for the set of positive images where each object in each image is marked by a rectangle and the corresponding coordinates of the rectangle are stored in a text file. These are then utilized for identifying features of the target and they are stored in a tree like structure in an XML file. Haar wavelet transform decomposes the input signals into a set of the basis function are called wavelets. Identify the relevant feature results is the easier, faster and better understanding of images. Relevant information of input data can be predicted by feature extraction. Algorithms are used to isolate and detect the shapes and desired portions significantly. The quality of the process of feature extracting affects the classification process. Thersholding helps to obtain the normal or abnormal images. Most effective techniques are used to isolate the object by converting in binary image from grey level and image with high contrast levels. The AdaBoost algorithm is a well-known method to build ensembles of classifiers with very good performance [28]. It is known empirically that AdaBoost with decision trees has excellent performance, being considered the best off-the-shelf classification algorithm.

**IV. PERFORMANCE EVALUATION**

In this section, we first introduce the three different datasets created by the user and evaluation measure that will be used for our proposed methods. Then the parameters setup is discussed before evaluating the experiments. In the end, we

will analyse the performance of the proposed framework with that of four different datasets are involved.

**A. Data Set**

For video based MVDT systems, our evaluation method performed with four different datasets containing videos captured by a high resolution camera on road .So in order to evaluate the performance of the proposed system, we employ the private datasets like CARXX, MUV, LRY 2018 datasets in that names are released with respect to the year in which datasets are constructed and closely relates to the application of intelligent transportation system. Each dataset consists of training and testing sets of 4000 images and 6000 images are present in each datasets. There are 4 input videos with around 800 frames / images .The remaining frames or images which are present in the final dataset are used for testing.

**B. Evaluation Measure**

Four evaluation measures are employed for different stages of the system. In order to evaluate the detection performance, precision and recall measure is adopted and then tracking performance is adopted by using positions and speed of the objects accuracy .Finally classification ratios is achieved through objects classification of the vehicles position and its accuracy. The following formula is incorporated to calculate the accuracy of detection rate of each vehicle in global manner with different datasets .The precision –recall is a parametric curve that represents the trade-off between accuracy and noise. The basic form of the precision is attained by the fraction of retrieved frames that are relevant while recall is the fraction of the relevant frames that are retrieved. The formulation of the metrics is as follows

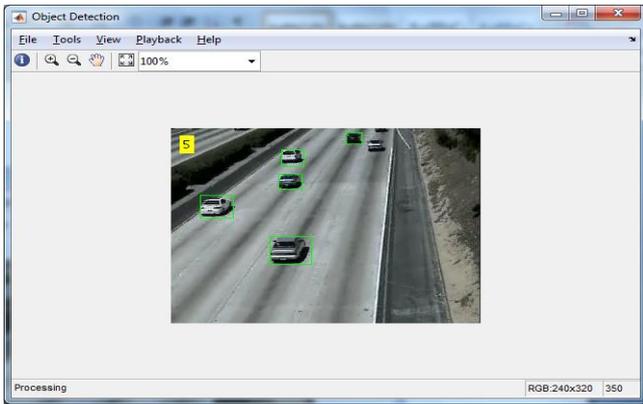
$$precision = \frac{TP}{TP + FP}, \quad recall = \frac{TP}{TP + FN}$$

$$Accuracy = \frac{TP + TN}{N}, \quad Specificity = \frac{TN}{N}$$

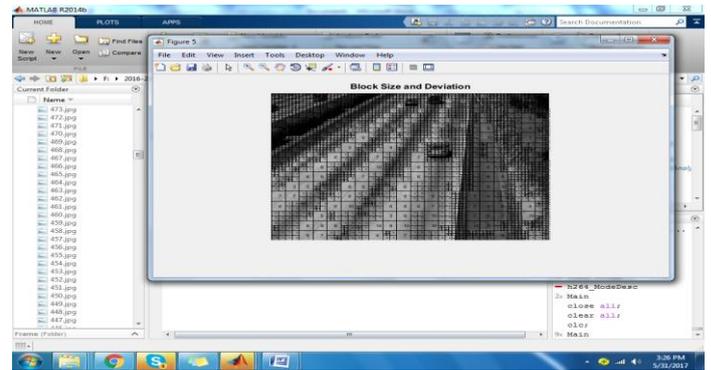
**Dataset 1**



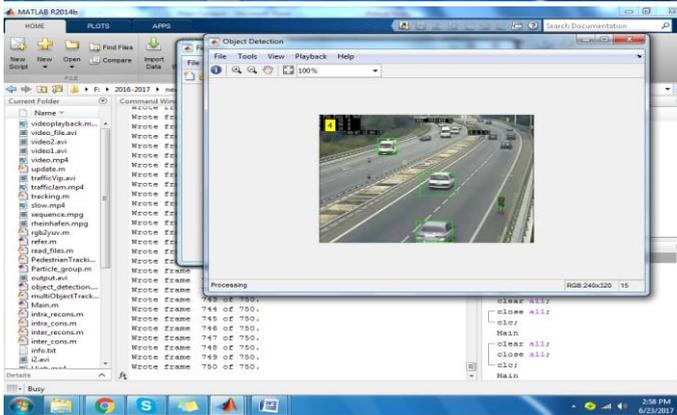
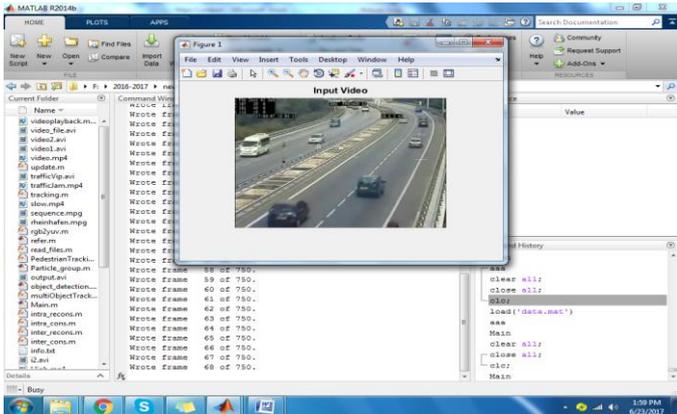
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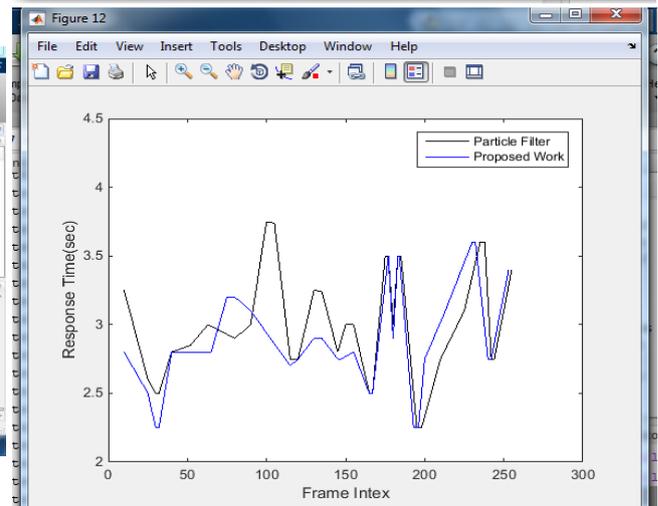
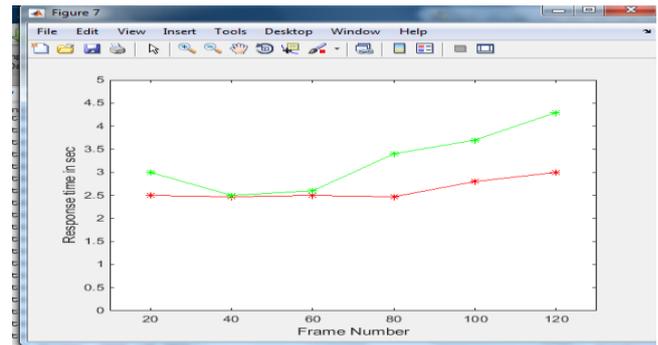
**Fig.3(a) CARSX Dataset Vs Detection of multiple cars**



**Fig.3(c) Datasets 1 Vs Object detection of Car and Block Size Deviation**



**Fig.3(b) CARSX Dataset Vs Detection of multiple cars in Non-Linear motion**



**Fig.4. Calculation of Response time Vs. Frame number**

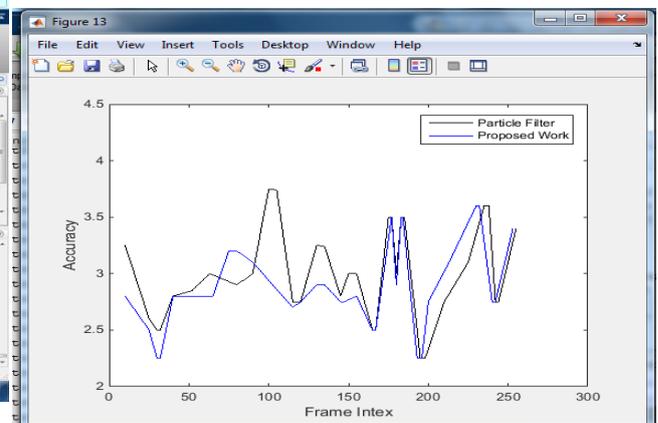
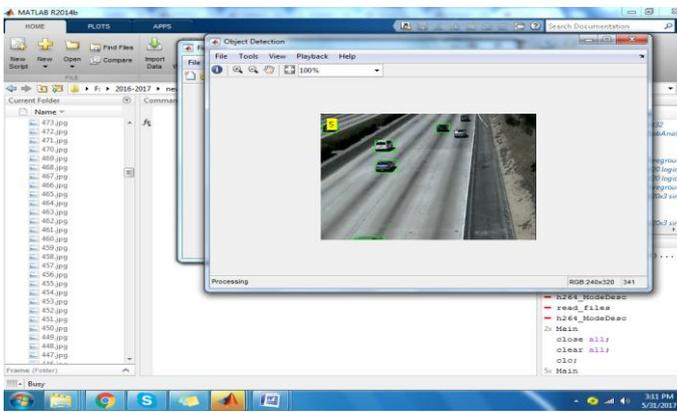




Fig.5.Calculation of Accuracy Vs. Frame number

In the fig.3(a) represents the CARX 2018 datasets and detection of multiple cars on road .The smaller the distance

is, the better accuracy will be.To compare the effect of the parameters handled in a multiple vehicle detections are as follows length, width, no of mirrors, height ,vehicles pattern, no of wheels and so on.With the greater parameters accuracy is obtained more in the detection rate as shown in graph Frame Index Vs accuracy and response time is also computed for car, bus and lorry in a different dataset.

**Dataset 2**

In the below fig.6 illustrates that multiple vehicle detection of Dataset 2 and corresponding graph represents the response time comparison of proposed work and particle filters in seconds. When the green colour line represents the proposed model and red colour line depicts the existing state of the art .If the number of objects increases on road then the accuracy gets increases by 30% as shown in fig.

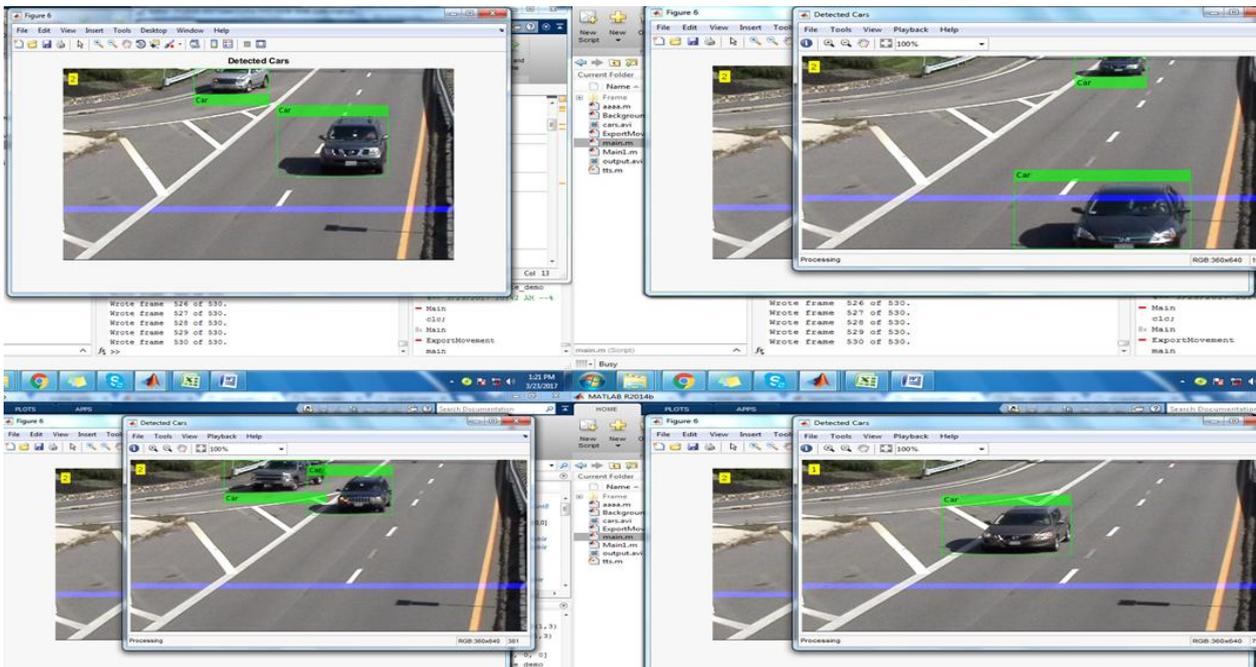


Fig.6. Results of the Proposed System for Data Set 2

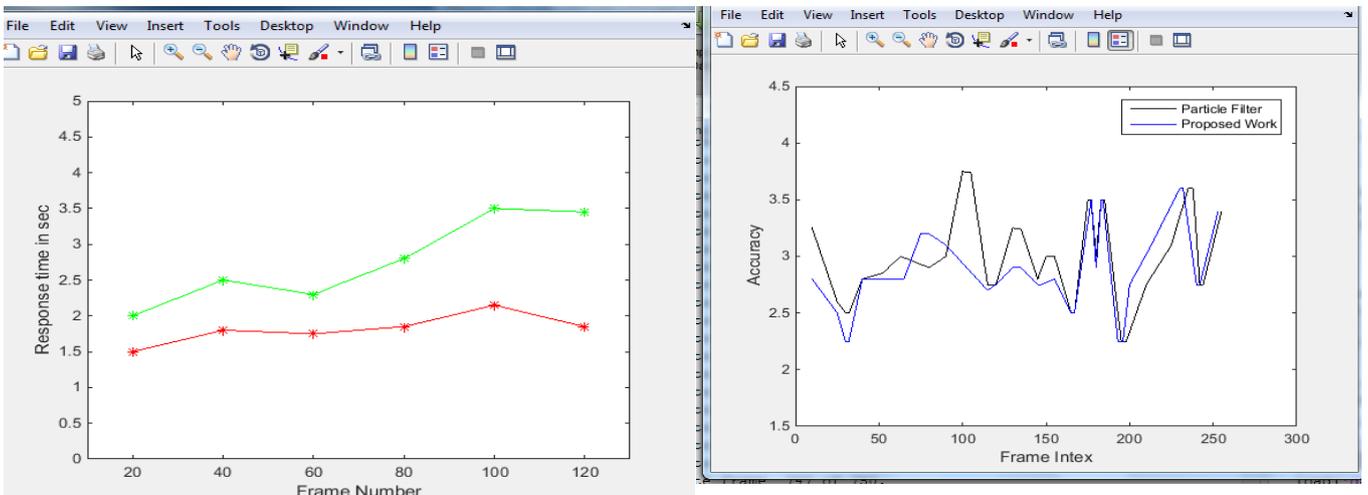


Fig.7.a) Response Time Comparison for Dataset 2 Fig 7.b) Response Time Comparison for Dataset 2

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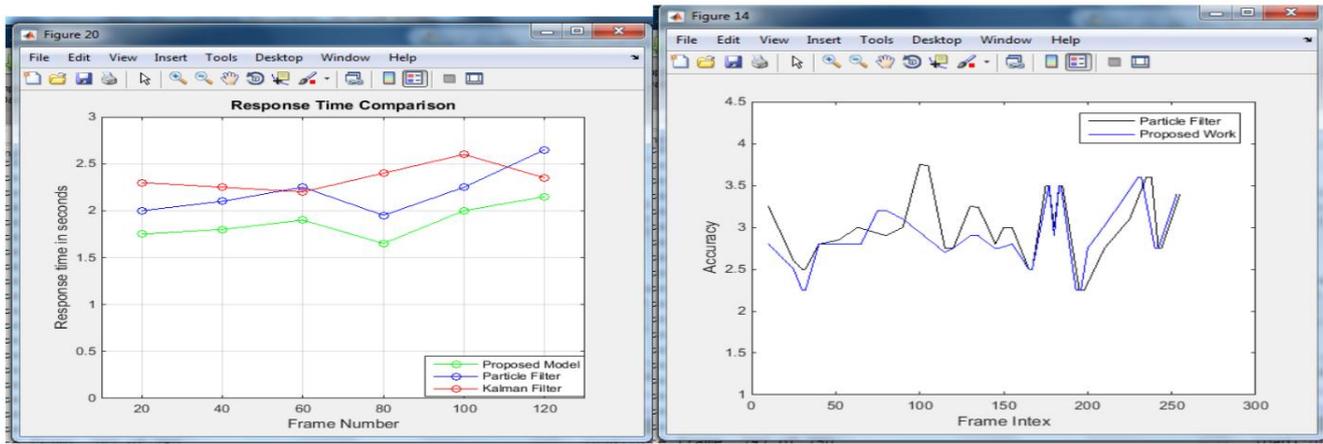


Fig.7(c) Response Time of Proposed Model for Dataset 2 Fig.7(d) AccuracyVs Frame Index for Dataset 2

## Dataset 3



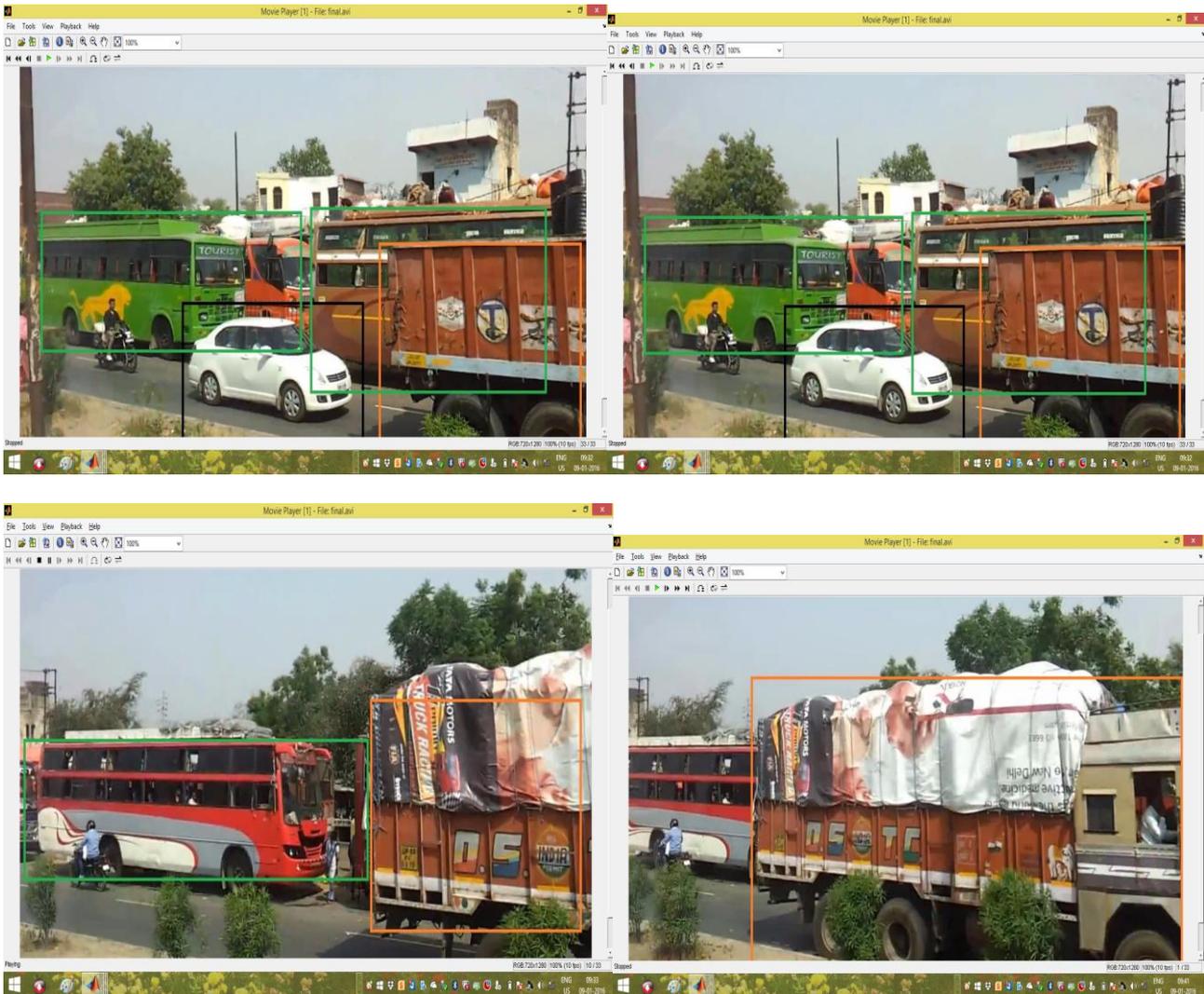


Fig.8.Proposed Results of Tracking in Linear Motion for Dataset 3

The accuracy of the proposed model for single object tracking for three different data sets on an average was found to be 85% but the missing detection rate were 26% on an average.

Table 3 Accuracy of Proposed Model for Single Object Tracking

Nature of the Dataset(SO)	Accuracy	False Positive Rate
LowNL	81.7%	28.7%
HighlyNL	84.1%	26.8%
HighlyL	89.5%	22.5%

SO – Single Object, L- Linear, NL- Non-linear

SPEED ANALYSIS OF DIFFERENT RESOLUTIONS FOR SINGLE OBJECT TRACKING

Table 4 Speed Analysis for Single Object Tracking

Dataset	Video Resolution	Object Size	Speed
I	420X240	282x92	9~11 fps
II	640X480	130x105	13~15 fps
III	640X480	120x55	12~15 fps

The speed of the proposed model was analyzed by subjecting the system to different datasets where the object size was variable in nature. On an average it was found that the speed of the tracking (Table 4) in case of single object was found to be as high as 13 fps. This is approximately 46% increase in speed in comparison to the approach proposed in [20].

## V. CONCLUSION

The experimental results and the inferences show that the method proposed clearly estimates the information about the object region with the help of the machine aware system learning, particle grouping and bus topology approach. Though the nature of the particle filter allows for efficient processing of a non-linear system, implementation becomes quite slow for real time problems because of handling of symbolic constants and thus needs a lot of calculation time. As an example, when particle filter was applied to the data set 1, the average response time was found to be 2.31s while that of the proposed system was as less as 1.43s. The particle grouping technique in comparison with the traditional application of the particle filter has halved the number of particles that are required to be processed for tracking. For example, for a frame of resolution 350x240, a total of 2040 particles are required. But in the proposed system, due to grouping of particles it is reduced to 1050 particles which is approximately 50% reduction in computation. On an average there is a 40% increase in performance of the system and it is proved to be effective under different aforementioned scenarios, while Kalman filter fails abruptly in tracking the objects under non-linear motion. Also the accuracy in tracking the moving objects under various types of occlusion has been enhanced by 30% due to the superposition estimation and distance formulation techniques in comparison with the other filters. Also Kalman filter has an appreciable false tracking rate which degrades the working of the system. Although Particle filter handles partial occlusion, its computational complexity increases exponentially with a need for a number of particles for processing. But on applying the proposed particle grouping method, the number of computations is almost halved as in the case of dataset 1.

## REFERENCES

- Pan Pan and Dan Schonfeld, 'Video Tracking Based on Sequential Particle Filtering on Graphs', IEEE Transactions on Image Processing, 16 May 2011, Vol. 20, No. 6, PP.1641-1651.
- Scott McCloskey, Michael Langer, and Kaleem Siddiqi, 'Removal of Partial Occlusion from Single Images', IEEE Transactions on Pattern Analysis and Machine Intelligence, 17 January 2011, Vol. 33, No.3, PP.647-654.
- Aniruddha Kumbhavi, David Harwood and Larry S. Davis, 'Vehicle Detection Using Partial Least Squares', IEEE Transactions on pattern analysis and machine intelligence, 19 April 2011, Vol. 33, No. 6, PP.1250 – 1265.
- Tie Liu, Zejian Yuan, Jian Sun, Jingdong Wang, Nanning Zheng, Xiaou Tang and Heung-Yeung Shum, 'Learning to Detect a Salient Object', IEEE Transactions on Pattern Analysis and Machine Intelligence, 20 December 2010, Vol. 33, No. 2, PP.353-367.
- Behrooz Sadeghi, Behzad Moshiri, 'Second-order EKF and Unscented Kalman Filter Fusion for Tracking Maneuvering Targets', IEEE Conference on Information Reuse and Integration, 4 September 2007, PP.514-519.
- Bohyung Hun and Lrry Duvis, 'Object tracking by adaptive feature extraction', International Conference on Image Processing, 18 April 2005, Vol 3, PP.1501 - 1504.
- Bo-Hao Chen, Ling-Feng Shi and Xiao Ke, 'A Robust Moving Object Detection in Multi-Scenario Big Data for Video Surveillance', IEEE Transactions on Circuits and Systems For Video Technology, 2018.
- Zhipeng Deng, Hao Sun, Shilin Zhou, Juanping Zhao and Huanxin Zou, 'Towards Fast and Accurate Vehicle Detection in Aerial Images Using Coupled Region-Based Convolutional Neural Networks', IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, August 2017, Vol. 10, No.8, PP.3652-3664.
- Keyu Lu, Jian Lu, Li Zhou, Xiping Hu, Xiangjing An and Hangen He, 'Generalized Haar Filter-Based Object Detection for Car Sharing Services', IEEE Transactions on Automation Science and Engineering, October 2018, Vol. 15, No. 4, PP.1448-1458.
- YingFeng Cai, Hai Wang, Zhengyang Zheng and Xiaoliang Sun, 'Scene-Adaptive Vehicle Detection algorithm Based on a Composite Deep Structure', IEEE Access, 26 September 2017, Vol.5, PP.22804-22811.
- Ravikumar Satzoda and Mohan Manubhai Trivedi, 'Multipart Vehicle Detection Using symmetry-Derived analysis and Active Learning', IEEE Transactions on Intelligent Transportations Systems, April 2016, vol.17, N.O.4, PP.926-937.
- Akshay Rangesh, Eshed Ohn-Bar and Mohan Manubhai Trivedi, Fellow, "Long -Term Multi cue Tracking of Hands in Vehicles", IEEE Transactions on Intelligent Transportation Systems, vol.17, No.5, pp.no.1483-1492, 2016.
- Dominik Kellner, Michael Bajrenbruch, Jens Klapstein and Klaus Dietmayer, Member, IEEE, "Tracking of Extended objects with High-Resolution Doppler Radar", IEEE Transactions on Intelligent Transportation Systems, vol.17, No.5, pp.no.1493-1509, 2016
- Harish Baskar, Kartik Dwivedi, Debi Prasad Dogra, Mohammed Al-Mualla, Lyudmila Minaylova, "Autonomous detection and tracking under illumination changes, occlusions and moving camera", signal processing, 2015, vol.no.155, pp.no.343-354.
- Hamid Hassannejad, Paolo Medici, Elenca cardarelli Pietro Cerri, "Detection of moving objects in roundabout based on monocular system", Experts system with applications, 2015, vol.42, pp.no.4167-4176.
- Sebastiano Battiato, Giovanni Maria Farinella, Antonino Furnari, Giovanni Puglisi, Anique Snijders, Jelmer Spiekstra, "An integrated system for vehicle tracking and classification", Experts systems with Applications, Vol .7, pp.no.7275,2015.
- Na Zhao, Yingjie Xia, Chao Xu, Xingmin Shi, Yuncai Liu, "Appos: An adaptive partial occlusion segmentation method for multiple vehicles tracking", J.vis.commun.Image.R..2015.
- Chieh-Chih Wang, Charles Thorpe and Arne Suppe, "Ladder based detection and tracking of moving objects from a ground vehicle at high speeds", IEEE, 2015, 416-421.
- A. Alahi, M. Bierlaire, P. Vandergheynst, "Robust real-time Pedestrians detection in urban environment with low-resolution cameras", Transportation Research part c, vol 39, 2014, pp.no 113-128.
- Taewung Kim and Hyun- Yong Jeong, "A novel algorithm for crash detection under general road scenes using crash probabilities and an interactive multiple model particle filter", IEEE Transactions on Intelligent Transportation systems, vol.15, no.6, Dec 2014, 2480-2490.
- Bin Tian, Ye Li, Bo Li, and Ding Wen, "Rear-View Vehicle Detection and Tracking by Combining Multiple Parts for Complex Urban Surveillance", IEEE Transactions On Intelligent Transportation Systems, Vol.15, No. 2, pp.no.597-606, 2014.
- Shuguang Li, Hongkai Yu, Jingru Zhang, Kaixin Yang, Ran Bin, "Video-based traffic data collection system for multiple vehicle types", IET Intelligent Transport Systems, Vol. 8, Issue. 2, pp.no. 164-174, 2014.

23. Taewung Kim and Hyun-Yong Jeong “A Novel Algorithm for Crash Detection under General Road Scenes Using Crash Probabilities and an Interactive Multiple Model Particle Filter “IEEE Transactions on Intelligent Transportation Systems, Vol. 15, No. 6, pp.no.2480-2490, 2014.